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Combined domestic demand response and energy hub optimisation with renewable generation uncertainty

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Abstract

The optimisation of energy hub modelling at domestic level exploits the redundancy of multiple energy carriers against customers' stochastic demand profiles, and thus increases system flexibility. On the other hand, demand response enables the shifting of deferrable appliances in response to energy carrier price to minimize the system cost and maintain customers' comfortability. Combining demand response schemes with energy hub approach yields further energy cost saving. However, the optimal operation of energy hub system may be affected by stochastic elements. In this paper, the uncertainty of solar radiation is modelled by 2 point estimated method and applied to an energy hub with demand response optimisation. The results demonstrate that incorporating demand response to energy hub optimisation brings 4% of additional energy cost saving for a single energy hub system, and that greater savings can be foreseen for large scale system.

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Keywords: Demand Response; Energy Hub Optimisation; Mixed Integer Linear Programming; 2 Point Estimated Method

1. Introduction

Domestic buildings consume approximately 40% of total society's energy [1, 2]. However, energy efficiency is reduced due to losses during transmission and distribution. The energy hub approach is a viable solution to increase energy efficiency and minimize system cost at domestic level. The energy hub concept coordinates the utilization of multiple energy carriers to optimize the system for minimal energy cost or carbon emissions [3]. From a customer's

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perspective, the utilization of co-generation or tri-generation increases system flexibility by means of exploiting every available energy carrier, whose monetary or environmental cost may be time-dependent. For example, the utilization of different energy carriers could be accordingly adjusted to satisfy the energy demand against time-variant energy tariffs. The energy hub approach at residential level has been the focus of much research. In [4] and [5], a single family house and a group of three houses are modelled as an energy hub system, and a model predictive control (MPC) scheme is applied to optimally determine the system operations. Reference [6] formulates a novel mathematical model for appliances, storage, and renewable generators in a residential hub, and mixed integer linear programming (MILP) method is applied to optimize the energy hub with the consideration of end-user preferences.

On the other hand, demand response schemes are widely employed by domestic customers to shift flexible loads in response to the variation of electricity tariffs to reduce electricity cost or maximize user comfort levels [7]. The energy hub approach provides an enhanced solution for demand response since the electricity demand may be satisfied by exploiting other energy carriers with low costs. Therefore, combining energy hub optimisation and demand response scheme is likely to yield further energy cost saving.

The uncertainty of solar radiation is also considered in this paper. The solar PV generation at each time step is modelled by a random number to reflect the stochastic nature of solar radiation. Much research has been undertaken to model uncertainty elements. Monte Carlo methods have been widely applied to solve the optimal energy management problem with uncertainty [8, 9]. However, the utilization of Monte Carlo methods suffers from high computational burden. To effectively solve the optimisation problems with uncertainties, other modelling methods are proposed. References [10, 11] apply robust optimisation to model the uncertainty, where forecasting techniques are used to build confidence intervals of uncertainty data based on historical data. Additionally, the stochastic data can be modelled by various scenarios to an acceptable level (e.g. 10 scenarios), and each scenario corresponds with a specific probability. Two-stage stochastic programming may be applied to solve the optimisation problem under each scenario [12, 13]. The 2 point estimated method (2PEM) [14] is applied in this paper to simulate the uncertainty of solar radiation into scenarios, and deterministic optimisation can be implemented for each scenario.

This paper is organized in six sections. Following the introduction, the modelling of the domestic energy hub and the solar radiation uncertainty is introduced in section 2. Section 3 describes the demand response scheme. The optimisation problem is formulated in section 4, and the related results are discussed in section 5. Section 6 concludes the paper and suggests future work.

2. Energy hub modelling

A typical residential house is modelled as an energy hub system as shown in Fig. 1. Heating converters including a gas boiler and a micro-CHP are equipped within the hub. Solar photovoltaics (solar PV) are also installed in the energy hub system, and the modelling of solar generation uncertainty is discussed in this section.

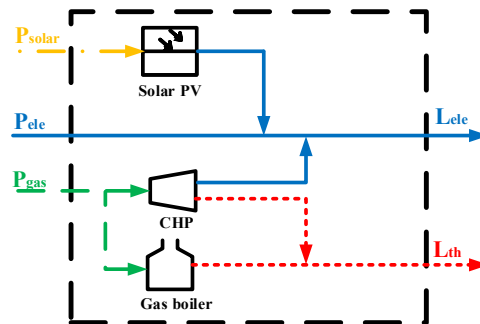


Fig. 1. Single energy hub system

As indicated in Fig. 1, the energy hub consumes solar energy, electricity, and gas through solar PV, micro-CHP, and a gas boiler to satisfy the electricity load L_{elec} and heat load L_{th} . The relation between hub output and input is formulated with a coupling matrix as indicated in equation (1).

The first matrix on the right hand side is the coupling matrix, each element in the matrix represents the relation between hub output and related energy carrier input. The parameter t within the brackets indicates the variables are time dependent. L_{elec} and L_{th} represent the electricity demand and heat demand of the residential hub, P_{so} , P_{elec} , and P_{gas}

$$\begin{bmatrix} L_{ele}(t) \\ L_{th}(t) \end{bmatrix} = \begin{bmatrix} \eta_{so} & 1 & v(t) \times \eta_e \\ 0 & 0 & v(t) \times \eta_{th} + (1-v(t)) \times \eta_{bo} \end{bmatrix} \times \begin{bmatrix} P_{so}(t) \\ P_{ele}(t) \\ P_{gas}(t) \end{bmatrix} \quad (1)$$

denote the solar energy, electricity, and gas input. η_{so} and η_{bo} indicate the efficiency of solar PV and gas boiler. η_e and η_{th} are the electric efficiency and thermal efficiency of the micro-CHP. The variable v is the dispatch factor, which determines the ratio of energy injected to a certain converter. In this case, v represents the ratio of gas injected to micro-CHP over total gas injection P_{gas} . The power and gas injection to the hub at each time step are limited within the safety boundaries and indicated in (2) and (3). The restriction for dispatch factor is shown in (4).

$$P_{ele,min}(t) \leq P_{ele}(t) \leq P_{ele,max}(t) \quad (2) \quad P_{gas,min}(t) \leq P_{gas}(t) \leq P_{gas,max}(t) \quad (3) \quad 0 \leq v(t) \leq 1 \quad (4)$$

2.1. Micro-CHP

The micro-combined heat and power system (micro-CHP) simultaneously generates heat and power, which is capable of reducing electricity consumption and increasing energy efficiency [15]. The micro-CHP electric capacity is generally below 15 kW, and thus suitable for a residential scale hub, providing an alternative source for the hub's electrical demand. The output of the micro-CHP modelled in this paper is assumed to be steady state with constant electric efficiency and thermal efficiency. The ramp rate of micro-CHP is considered as a constraint to restrict the power output, and it is shown in (5). The electric output is limited within the maximum and minimum value as shown in (6), where e_p denotes the micro-CHP electric output, and e_{ramp} represents the micro-CHP maximum ramp rate.

$$-e_{ramp} \leq e_p(t-1) - e_p(t) \leq e_{ramp} \quad (5) \quad e_{p,min} \leq e_p(t) \leq e_{p,max} \quad (6)$$

2.2. Uncertainty of solar PV generation

The uncertainty of solar radiation is represented by different scenarios generated by the 2PEM algorithm based on historical data. The random value of solar radiation at each time step can be replaced by two concentration points, and the two concentration points are located on the two sides of the mean value point. The mean value point is derived by averaging all historical data at this specific time step. The historical data adopted in this paper is on an hourly granularity. Therefore, there are 48 concentration points generated for a 24-hour simulation, with 2 points for each time step. Each concentration point E_t^k at time step t is included in each individual scenario, the other elements in the scenario are the mean value E_{mean}^t at other time steps. Hence there are 48 scenarios in total. The scenario X is denoted in (7). $k=1, 2$ represents the concentration number.

$$X = [E_{mean}^1, E_{mean}^2, \dots, E_t^k, \dots, E_{mean}^{24}] \quad (7)$$

3. Demand response

There are three types of appliances modelled to participate in the demand response scheme. The definition of these appliances and related mathematical formulation can be found in [16] and are illustrated in this section.

3.1. Nonflexible deferrable appliances

The expression *nonflexible deferrable appliances* indicate that the appliances are able to begin at any time based on customer's preference. However, once initiated, the appliances' operation at each time step will follow its predetermined consumption profile and must not be interrupted. Therefore, the objective of demand response is to find the best starting time for this type of appliance to maximally reduce the energy cost. The preferred starting time is determined by the customers and represented by a time period λ^d . The best starting time is characterized by a binary variable and denoted as x_t^d . $t \in T$ represents the time steps, $d \in D$ indicates the nonflexible deferrable appliances. x_t^d is restricted by (8).

$$\sum_{k \in \mathcal{A}^d} x_t^d = 1 \quad \forall d \in D \quad (8)$$

The optimized power profile of nonflexible deferrable appliances is expressed by shifting the original power profile to the best start time within the scheduling horizon. The appliance power consumption at each time step P_t^d is expressed in (9) in terms of the original power profile P_l^d and the binary variable x_t^d .

$$P_t^d = \sum_{l=0}^{N-1} P_l^d \times x_{t-l+1}^d \quad \forall t \in T, \forall d \in D \quad (9)$$

$l \in L$ also represents the time step, and it is an alias of time step $t \in T$. N is the number of total time steps.

3.2. Curtailable appliances

Curtailable appliances may be switched on or off, and it is not necessary to switch them on later. The customers can assign different level of priorities to operate curtailable appliances. The appliance power consumption at each time step P_t^i is expressed in (10) where $i \in I$ indicates the curtailable appliances.

$$P_t^i = s_t^i P^{i,rated} Occ_t^i \quad \forall t \in T, \forall i \in I \quad (10)$$

s_t^i represents whether the status of appliance is on or off at each time step, Occ_t^i denotes the preferred starting time decided by customers, and $P^{i,rated}$ indicates the rated power of appliance i .

3.3. Critical appliances

Critical appliances mean that the appliances are uncontrollable and without restrictions. The power consumed for critical appliances at each time step is denoted by P_t^c , where $c \in C$ represent the critical appliances.

Therefore, the total consumptions of all appliances at each time step is denoted as P_t^{tot} and illustrated in (11).

$$P_t^{tot} = P_t^i + P_t^c + P_t^d \quad \forall t \in T, \forall i \in I, \forall c \in C, \forall d \in D \quad (11)$$

4. Optimisation problem formulation

The optimisation is implemented for a single residential energy hub system over 24 hours' scheduling horizon with a 15-minute time step. The demand response scheme is applied to coordinate the energy hub optimisation to optimally determine the working status of the three types of appliances illustrated in section 3. The objective is to minimize the total system cost over the whole time horizon with the knowledge of energy carrier tariff, electricity and heat load, efficiency of converters, and the appliances preferred starting time determined by customers. The control variables $\mu(t)$ to be optimized at each time step t are indicated in (12).

$$\mu(t) = [P_{ele}(t), P_{gas}(t), v(t), P_t^i, P_t^c, P_t^d] \quad (12)$$

The optimisation problem is formulated in (13).

$$\begin{aligned} & \text{Minimize} \quad \sum_{t=1}^N [P_{ele}(t) \times \Pi_{ele}(t) + P_{gas}(t) \times \Pi_{gas}(t)] \\ & \text{subject to} \quad (1) - (6), (8) - (11) \end{aligned} \quad (13)$$

Note the electricity demand $L_{ele}(t)$ in (1) is replaced by appliances' total consumptions P_t^{tot} , to reflect that demand response is now part of the energy hub optimisation. The solar PV generation is modelled to 48 scenarios and each scenario corresponds with a specific probability. The optimisation for solving problem (13) is implemented for each scenario m , and the final optimisation results, f , considering the solar radiation uncertainties are derived by adding up the value of the optimisation results f_m for each scenario multiplied by the corresponding probability p_m (14). The final optimized operations $\mu(t)$ considering every scenario are derived in a similar way.

$$f = \sum_{m=1}^{48} (f_m \times p_m) \quad (14)$$

The scenarios generated for solar radiation is on an hourly basis, but the optimisation is on a 15 minute time step. Therefore, the data from solar radiation is divided by 4 and allocated to each time step to fit the overall optimisation.

5. Case study and results

5.1. System setup

The case study implements the optimisation for the energy hub system incorporating the demand response scheme for a house with 3 occupants in a typical winter day. The electricity load including the appliance consumptions and heat load are simulated based on [17] and [18]. The electricity tariff is obtained from the variant tariff in reference [19]. The gas price is assumed to be constant as £0.03 over 24 hours. The 48 scenarios representing the uncertainty of solar radiation over 24 hours are generated by 2PEM based on historical data obtained from [20]. The thermal and electric efficiency of the micro-CHP are assumed to be 0.57 and 0.33 respectively. The micro-CHP ramp rate is chosen as 0.15 kW/min, and the maximum electric output is 3 kW. The boiler efficiency is assumed to be 0.85.

A washing machine is modelled in the hub as a nonflexible deferrable appliance, and the predetermined profile of the washing machine is to operate for 150 minutes from 18:00. For the demand response scheme, the customer prefers to operate the washing machine at any time after 18:00. A hob with rated power of 2.65 kW and a microwave with rated power of 1.4 kW are simulated as curtailable appliances. The customer prefers to operate these appliances during 18:30–21:30 and 7:00–8:00 respectively. The optimisation problem (13) is thusly solved by applying mixed integer linear programming.

Three cases are simulated in this paper. In the first case, only the energy hub optimisation is carried out for the system. In the second case, the energy hub formulation is not considered, and the heat load is satisfied by the gas boiler, only demand response is implemented for the system in response to the electricity price. The demand response scheme is incorporated into the energy hub optimisation for the third case. The related results are shown below.

5.2. Results

The total energy cost over 24 hours for the three cases are £3.61, £4.39 and £3.48 respectively. To investigate the effectiveness of incorporating the demand response to the energy hub optimisation, the appliance consumptions over the whole time horizon derived from second case and third case are compared in Fig. 2, the appliance consumptions generated with [17] is also drawn for reference. The electricity tariff over 24 hours is shown in Fig. 3. The electric output from Micro-CHP derived from case three is presented in Fig. 4.

As shown in Fig. 2, the green line represents the original generated total appliance consumptions, the red line and the blue line indicate the appliance total consumptions obtained from case two and case three. The operations of the washing machine are compared for the two cases. The washing machine is predetermined to be operated from time step 73 to 82, the working time is shifted to the period 87 to 96 when the demand response is applied. It can be

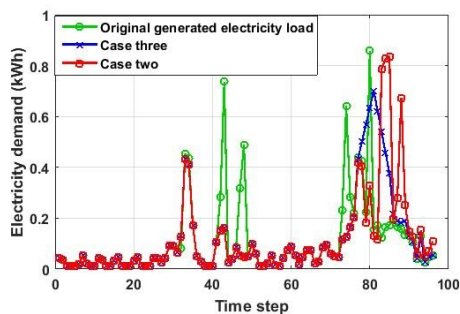


Fig. 2. Appliances consumptions comparison

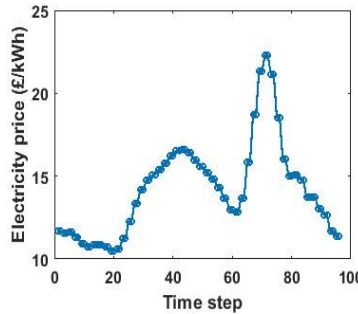


Fig. 3. Electricity price over 24 hours

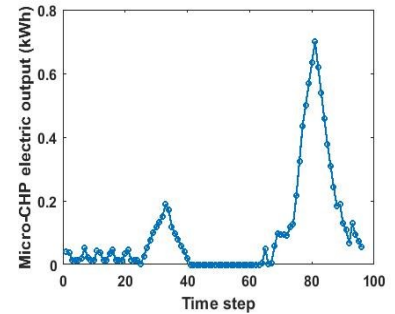


Fig. 4. Electricity output from Micro-CHP

concluded from Fig. 3 that the electricity price continues to drop after time step 74. Thus the demand response chooses to operate the washing machine in the final period to save the energy cost.

On the other hand, the washing machine starts operating from time step 80 in case three. It could be obtained from Fig. 4 that the micro-CHP is supporting the electricity demand after the 65th time step, and therefore despite the high electricity tariff, the demand response does not need to time shift the washing machine as it does in case 2. Since the micro-CHP is restricted by the ramp rate, the washing machine is able to run time step 80 when the operating status of micro-CHP reaches sufficient output to support both washing machine and other appliances.

6. Conclusion

This paper incorporates demand response to energy hub optimisation under the solar radiation uncertainty. The optimisation is applied to a 3 occupant household in a typical winter day. Three types of appliances are simulated within the demand response scheme. The total energy cost can be further saved for 4% when the demand response is incorporated to the optimisation. Therefore, more saving is foreseen when the optimisation scheme is applied to a higher level such as community level. Future work will be carried out to apply more accurate models to represent all types of appliances, and the probabilistic model to simulate uncertainty will be enhanced.

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